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IN THE UNITED STATES DISTRICT COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA
SAN FRANCISCO DIVISION

**STATE OF CALIFORNIA, by and through
Attorney General Xavier Becerra;
COUNTY OF LOS ANGELES; CITY OF
LOS ANGELES; CITY OF FREMONT;
CITY OF LONG BEACH; CITY OF
OAKLAND; CITY OF STOCKTON,**

Plaintiffs,

v.

**WILBUR L. ROSS, JR., in his official
capacity as Secretary of the U.S.
Department of Commerce; U.S.
DEPARTMENT OF COMMERCE; RON
JARMIN, in his official capacity as Acting
Director of the U.S. Census Bureau; U.S.
CENSUS BUREAU; DOES 1-100,**

Defendants.

3:18-cv-01865

**TRIAL DECLARATION OF BERNARD
L. FRAGA, PH.D.**

Dept: 3
Judge: The Honorable Richard G.
Seeborg
Trial Date: January 7, 2019
Action Filed: March 26, 2018

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1 **I. BACKGROUND AND QUALIFICATIONS**

2 1. My name is Bernard L. Fraga. I am a political data analyst and researcher. I am also
3 employed as an assistant professor of political science at Indiana University Bloomington, where
4 I joined the faculty in 2013.

5 2. I earned my Ph.D. in Government and Social Policy at Harvard University in 2013,
6 where my graduate training included courses in political science, statistics, and election law. I
7 also received my Master of Arts degree in Political Science from Harvard University in 2011, and
8 my Bachelor of Arts degree in Political Science and Linguistics from Stanford University in
9 2008.

10 3. My academic research focuses on American politics, with particular research interests
11 in elections, representation, and the demographic composition of the population where I
12 frequently analyze data provided by the U.S. Census Bureau. I have published peer-reviewed
13 works on these topics in the *American Journal of Political Science*, the *Journal of Politics*, the
14 *Journal of Race, Ethnicity, and Politics*, and the *Quarterly Journal of Political Science*. I have
15 also published work in the *Stanford Law Review*, and have a forthcoming book published by
16 Cambridge University Press. I have served as a peer reviewer for numerous academic journals
17 and press outlets in political science, advised multiple Ph.D. dissertations, and have been invited
18 to give many academic lectures regarding my work on elections, representation, and the
19 demographic composition of the population. My academic research has appeared in outlets such
20 as the *New York Times* and the *Washington Post*. I previously produced expert reports in *Perez v.*
21 *Texas* (2017) and *Common Cause Indiana et al. v. Marion County Election Board et al.* (2018).

22 4. Attached as **Exhibit A** to this Declaration is a true and correct copy of my complete
23 and current curriculum vitae.

24 **II. SCOPE OF WORK**

25 5. I was retained by Plaintiffs in this action to provide my expert opinion on the impact
26 of the addition of a question on citizenship status to the 2020 Census would have on the
27 population count for California, and California's congressional apportionment, which will be
28 based on the enumeration conducted as part of the 2020 Census. Specifically, I was asked:

- To project the population of California and other states at the time of the 2020 Census enumeration;
- To estimate, based on survey and Census Bureau data, the proportion of California's and other states' residents who would not be counted due to the addition of a citizenship question on the 2020 Census under four scenarios of nonresponse and follow-up;
- To quantify the probability that an undercount of California residents attributable to the addition of a citizenship question on the 2020 Census would decrease California's congressional apportionment.

6. My opinions explained herein in this declaration are based on my existing knowledge, expertise, and experience, along with the statistical analysis of a series of relevant data sources. To complete these statistical analyses, I used publicly available data provided by the U.S. Census Bureau, documents produced by the defendants in the course of this litigation, and results from a nationally representative survey. Specifically, I analyzed the following data sources:

- U.S. Census Bureau Population Estimates Program (PEP) estimates of the population, by state;
- U.S. Census Bureau American Community Survey (ACS) estimates of the population, by state, race, ethnicity, nativity, and citizenship of household members;
- U.S. Census Bureau apportionment population data for the 1980, 1990, 2000, and 2010 Census;
- Responses to items in the *Census 2020 Survey*, fielded by Dr. Matthew A. Barreto.

7. Attached as **Exhibit B** to this Declaration is a list of materials, including documents and publications, that I relied on when forming my expert opinion. These are the types of publications and documents that experts in this field would reasonably rely on when forming an expert opinion of this nature.

III. SUMMARY

8. Based on my analysis, I have formed the following opinions:

- a. First, based on the survey and Census Bureau data provided, compared to other states, California has a disproportionately high share of the population that would not be

1 enumerated in a 2020 Census that includes a citizenship question.

2 b. Second, using publicly available Census Bureau estimates, the best
3 estimates for the projected population of each state on April 1, 2020 indicate that California would
4 be apportioned 53 seats in the U.S. House of Representatives if the 2020 Census does not include a
5 citizenship question.

6 c. Third, the addition of a citizenship question to the 2020 Census is likely
7 to reduce the congressional representation apportioned to California.

8 d. Fourth, under a broad range of potential April 1, 2020 population
9 estimates for each of the states, and methods of quantifying the undercount, the addition of a
10 citizenship question always increases the probability of California receiving fewer congressional
11 seats than in a 2020 Census with no citizenship question.

12 9. The above findings persist even with uncertainty inherent in making population
13 projections, uncertainty in the demographic composition of states, survey sampling error, and
14 reasonable efforts to follow up with nonresponding households.

15 **IV. PROJECTING A BASELINE ESTIMATE OF THE 2020 POPULATION THAT WOULD BE**
16 **ENUMERATED BY A 2020 CENSUS THAT DOES NOT INCLUDE A CITIZENSHIP**
17 **QUESTION**

18 10. In order to understand the impact of the addition of a citizenship question to the 2020
19 Census, I first constructed projections of each state's population for April 1, 2020 ("Census
20 Day"). The goal of the population projections is to generate a baseline estimate of the population
21 that would be enumerated by a 2020 Census that does not include a citizenship question.

22 11. To create statistical forecasting models, I started with the annual estimates of each
23 state's population publicly available through the Census Bureau's Population Estimates Program
24 (PEP).¹ These estimates "update the decennial census counts" and correspond to the July 1
25 population for each year after a decennial census, taking into account "births, deaths, Federal tax
26 returns, medicare [*sic*] enrollment, and immigration."² The Census Bureau notes that these figures

27 ¹ U.S. Census Bureau, Population and Housing Unit Estimates, available at:
28 <https://www.census.gov/programs-surveys/popest.html>.

² U.S. Census Bureau, Population and Housing Unit Estimates, Frequently Asked
 Questions, available at: <http://www.census.gov/programs-surveys/popest/about/faq.html>. (PTX-

1 are used in “Federal funding allocations, in setting the levels of national surveys, and in
2 monitoring recent demographic changes.”³

3 12. I used two sets of PEP estimates in my analysis. The first, more recent set is identified
4 as “Vintage 2017” by the Census Bureau and was released in June 2018.⁴ This dataset provides
5 updated estimates of the annual population of each state from July 1, 2010 to July 1, 2017, along
6 with the population count as enumerated in the 2010 Census. These population estimates are
7 based on the 2010 decennial Census, which did not include a citizenship question.

8 13. The second, older dataset is “Vintage 2007,” which was released in 2008.⁵ The older
9 dataset provides estimates of the annual population of each state from July 1, 2000 to July 1,
10 2007. Unlike the Intercensal or Postcensal estimates for 2000-2010, which also provide annual
11 estimates of the population before the 2010 Census, the Vintage 2007 PEP estimates are not
12 adjusted to provide smoothed trends in the population between 2000 and 2010.⁶ Thus, the Vintage
13 2007 PEP estimates are an analog to the Vintage 2017 PEP estimates calculated at roughly the
14 same period of time prior to the decennial census that followed, and can be used to estimate how
15 much error exists when comparing the projection to the true enumeration found in the Census.

16 14. Next, I compared several forecasting models to select which one would most
17 accurately predict the states’ populations on Census Day, April 1, 2020. Different modeling
18 approaches may reach different conclusions regarding this population, but forecasting approaches
19 generally consist of using trends in historical data to predict future trends as accurately as
20 possible.⁷ Drawing on principles of forecasting and my knowledge of methods of extrapolating
21 and interpolating Census data, I evaluated the accuracy of four forecasting models when using

22 583.)

23 ³ *Id.*

24 ⁴ U.S. Census Bureau, Data, State Population Totals and Components of Change: 2010-
2017, available at: <https://www.census.gov/data/datasets/2017/demo/popest/state-total.html>.

25 ⁵ U.S. Census Bureau, Data Sets, available at: <https://www2.census.gov/programs-surveys/popest/datasets/2000-2007/state/asrh>.

26 ⁶ U.S. Census Bureau, Methodology for the Intercensal Population and Housing Unit
27 Estimates: 2000 to 2010 (Revised October 2012), available at:
28 <https://www2.census.gov/programs-surveys/popest/technical-documentation/methodology/intercensal/2000-2010-intercensal-estimates-methodology.pdf>.
(PTX-583.)

⁷ See Rob J. Hyndman & George Athanasopoulos, *Forecasting: Principles and Practice*
(2018), available at <https://otexts.org/fpp2/index.html>.

1 Vintage 2007 data to project the Census 2010 population, and cross-checked those projections
2 with the actual 2010 Census count. The four forecasting models include the following:

3 a. Linear model from 2000-2007. In this model, I projected the population to
4 April 1, 2010 assuming a linear trend in the population for each state from July 1, 2007 to April 1,
5 2010 that is equivalent to the linear trend witnessed from July 1, 2000 to July 1, 2007. The
6 theoretical implications of this model are that prior trends in population change should continue at
7 the same linear rate that was witnessed since the 2000 Census. These estimates were generated
8 using a bivariate linear regression model with data from the Vintage 2007 PEP for each state via
9 the statistical software program R.

10 b. Weighted linear model from 2000-2007. In this model, I projected the
11 population to April 1, 2010 assuming a linear trend in the population for each state from July 1,
12 2007 to April 1, 2010 that is equivalent to the weighted linear trend witnessed from July 1, 2000
13 to July 1, 2007. This model incorporates the longer-term data from the first model, but gives more
14 weight to years that are closer to the end point of interest (2010). Weights are the inverse of the
15 number of years prior to 2010. These estimates were generated using a weighted linear regression
16 model with data from the Vintage 2007 PEP for each state via the statistical software program R.

17 c. Change from 2006-2007. The previous approaches average over multiple time
18 points in order to project the population. Instead, in this model, I isolated the difference between
19 the July 1, 2007 population and the July 1, 2006 population for each state, and then project this
20 change to April 1, 2010 assuming that the yearly change going forward will be equivalent to the
21 most recent yearly change in population. Here, I assumed that the last year of data provides the
22 best projection for the next three years of population change. These estimates were generated by
23 multiplying this short term trend by 2.75 and adding the result to the July 1, 2007 population.

24 d. Exponential smoothing. Instead of relying on linear or weighted linear trends in
25 the data, more complex forecasting methods are often used to predict future outcomes. Many of
26 these use smoothing techniques that account for nonlinearities in the data and generally do not
27 force the data to take a particular form. These models use the entire time period, but give more
28 weight to observations that are closer to the target end point (in this case, 2010). With exponential

smoothing, I assumed an additive trend in the data, and no seasonality in population totals. These estimates were generated using the *ets* function from the *forecast* package in the statistical software program R, again drawing on Vintage 2007 PEP data for each state.

15. To evaluate the accuracy of those four models, I compared each model's predicted April 1, 2010 population to the population count enumerated by the 2010 Census. I used three metrics to make my determination of accuracy: the mean difference between the projection and the actual count across states ("Mean Error"), the mean absolute value of the difference between the projection and the actual count ("Mean Absolute Error"), and the mean absolute error rescaled to be proportional to each state's 2010 Census count ("Mean Absolute Proportional Error").

16. The results of those comparisons are reflected in Table 1. Smaller values for the three evaluation metrics indicate less error in predictions.

17. Table 1: Validation of Population Projection Models from 2000-2007 PEP Data

	Mean Error	Mean Absolute Error	Mean Absolute Proportional Error
Linear Model	6,429	82,730	0.016
Weighted Linear Model	7,315	77,682	0.015
Change from 2006-2007	14,864	58,796	0.012
Exponential Smoothing	1,526	60,047	0.011

Note: Based on projections to the April 1, 2010 population made from Vintage 2007 Population Estimates Program (PEP) estimates. Analysis conducted by Bernard L. Fraga.

18. The exponential smoothing model best predicts the 2010 Census population using Vintage 2007 data because, as shown in Table 1, the mean error is the smallest, the mean absolute error is the second smallest, and the mean absolute proportional error is the smallest.

19. Differences between models are relatively small, indicating that model selection does not produce large differences in projections. However, for all of the models there is uncertainty in the projection of the population based on estimates from three years prior to Census Day. This uncertainty may manifest for any number of reasons, including the possibility of rapid change in a state's population a short time before Census enumeration takes place that would not be possible to account for under any modeling scenario. I accounted for this uncertainty in my population

1 projections by using the observed imprecision in the Vintage 2007-based modeling of the 2010
2 population. Specifically, the mean state 2010 projection was 0.3% lower than the Census 2010
3 enumeration, an exceptionally small difference. The standard deviation of this difference was
4 0.0161, which means that approximately 68% of states' projections of the 2010 population were
5 within 1.6% of the observed Census 2010 enumeration. I used this measure of state-level
6 projection uncertainty when calculating apportionment, but provide mean estimates of the
7 population in the following section.

8 20. Having determined the exponential smoothing forecasting model to be more accurate
9 than the other models, I used exponential smoothing to project each state's population by Census
10 Day, April 1, 2020. I ran the Vintage 2017 PEP estimates of the population of each state from
11 July 1, 2010 to July 1, 2017 through the exponential smoothing model to arrive at the 2020
12 Census Day projections. The results of this forecasting estimation process may be found in the
13 column labeled "2020 Projection" in Table 2. I also included in Table 2 the 2010 Census
14 enumeration for each state, and the July 1, 2017 PEP resident population.

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21. Table 2: Population by State in 2010, 2017, and 2020

	2010 Census	2017 PEP	2020 Projection
Alabama	4,779,736	4,874,747	4,909,797
Alaska	710,231	739,795	742,898
Arizona	6,392,017	7,016,270	7,302,219
Arkansas	2,915,918	3,004,279	3,041,609
CALIFORNIA	37,253,956	39,536,653	40,393,990
Colorado	5,029,196	5,607,154	5,793,650
Connecticut	3,574,097	3,588,184	3,582,310
Delaware	897,934	961,939	984,226
District of Columbia	601,723	693,972	727,258
Florida	18,801,310	20,984,400	21,668,695
Georgia	9,687,653	10,429,379	10,696,376
Hawaii	1,360,301	1,427,538	1,434,604
Idaho	1,567,582	1,716,943	1,817,286
Illinois	12,830,632	12,802,023	12,710,600
Indiana	6,483,802	6,666,818	6,735,594
Iowa	3,046,355	3,145,711	3,182,422
Kansas	2,853,118	2,913,123	2,932,387
Kentucky	4,339,367	4,454,189	4,491,934
Louisiana	4,533,372	4,684,333	4,722,625
Maine	1,328,361	1,335,907	1,331,859
Maryland	5,773,552	6,052,177	6,136,606
Massachusetts	6,547,629	6,859,819	6,973,938
Michigan	9,883,640	9,962,311	10,041,036
Minnesota	5,303,925	5,576,606	5,672,759
Mississippi	2,967,297	2,984,100	2,981,765
Missouri	5,988,927	6,113,532	6,153,347
Montana	989,415	1,050,493	1,067,836
Nebraska	1,826,341	1,920,076	1,951,944
Nevada	2,700,551	2,998,039	3,158,362
New Hampshire	1,316,470	1,342,795	1,358,014
New Jersey	8,791,894	9,005,644	9,073,181
New Mexico	2,059,179	2,088,070	2,093,728
New York	19,378,102	19,849,399	19,917,386
North Carolina	9,535,483	10,273,419	10,515,309
North Dakota	672,591	755,393	783,517
Ohio	11,536,504	11,658,609	11,756,941
Oklahoma	3,751,351	3,930,864	4,000,423
Oregon	3,831,074	4,142,776	4,310,660
Pennsylvania	12,702,379	12,805,537	12,804,528
Rhode Island	1,052,567	1,059,639	1,064,874
South Carolina	4,625,364	5,024,369	5,201,635
South Dakota	814,180	869,666	889,060
Tennessee	6,346,105	6,715,984	6,826,163
Texas	25,145,561	28,304,596	29,403,076
Utah	2,763,885	3,101,833	3,211,388
Vermont	625,741	623,657	621,076
Virginia	8,001,024	8,470,020	8,629,657
Washington	6,724,540	7,405,743	7,617,840
West Virginia	1,852,994	1,815,857	1,781,002
Wisconsin	5,686,986	5,795,483	5,837,508
Wyoming	563,626	579,315	598,982

Note: 2020 Projection is population projection to April 1, 2020 conducted by Bernard L. Fraga.

22. The state-level 2020 population projections shown in Table 2 form my baseline estimate of how many individuals would be enumerated by the 2020 Census if it contains the same content as the 2010 Census, that is, without a question on citizenship status.

23. California, like most other states, is projected to have a substantial increase in population between July 1, 2017 and April 1, 2020. Over three million more Californians should be enumerated in 2020 than were enumerated in 2010.

V. ESTIMATING THE UNDERCOUNT IN THE 2020 CENSUS DUE TO A CITIZENSHIP QUESTION

24. Starting with the baseline 2020 population projections, I next calculated estimates of the undercount in the 2020 Census that would occur specifically due to the addition of a citizenship question.

25. Here, the “undercount” is conceptualized as the net population effect of households not responding to the Census as a result of the citizenship question. This corresponds to the household being the basic unit of the enumeration universe for the Census Bureau and the basic unit when determining initial nonresponse to the Census.⁸ To estimate the undercount, I sought to identify and isolate the undercount attributable *only* to the addition of a citizenship question, not the broader undercount of certain populations that has disproportionately lowered the population for certain states, including California, in previous censuses.⁹

26. In order to estimate the effect of the addition of a citizenship question to the 2020 Census, I was asked by Plaintiffs’ counsel to explore four different scenarios of nonresponse and

⁸ See, e.g., *2020 Census Detailed Operational Plan for: 18, Nonresponse Followup Operation (NRFU)*, April 16, 2018, pgs. 4,72 (“The enumeration universe is the complete set of addresses for living quarters that will be enumerated for the 2020 Census. The NRFU Universe is a subset of that enumeration universe.”), pg. 4, cont. (“It comprises the set of addresses for living quarters that are housing units...for which the Census Bureau has not yet received a response.”) (PTX-539); Albert E. Fontenot, Jr., *2020 Census Program Memorandum Series: 2018.10*, April 16, 2018, (“The primary purpose of NRFU is to determine the housing unit status of a nonresponding address and to enumerate the households at nonresponding housing units.”), available at https://www2.census.gov/programs-surveys/decennial/2020/program-management/memo-series/2020-memo-2018_10.pdf (PTX-583).

⁹ See, e.g., Thomas Mule, “Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States,” DSSD 2010 Census Coverage Measurement Memorandum Series, 2010-G-01, May 22, 2012, pgs. 21-22. (PTX-211; AR 11390.)

1 nonresponse follow-up (NRFU). Those four scenarios are explained in detail below.

2 **A. Scenarios A and B: Estimating the Undercount Based on Survey Data from**
 3 **Dr. Matt Barreto**

4 27. Scenarios A and B are based on nonresponse and follow-up as indicated by the
 5 nationally-representative *Census 2020 Survey*, fielded by Dr. Matt Barreto and detailed in his
 6 expert report. (PTX-499.)

7 **1. Scenario A: Survey-based Nonresponse**

8 28. Scenario A determines the undercount using the estimate of specific nonresponse
 9 attributable to the addition of a citizenship question gathered from Dr. Barreto's survey data.

10 29. To gauge that nonresponse rate, Dr. Barreto's survey asked a series of questions
 11 providing measures of whether or not respondents would complete the Census for members of
 12 their household. Specifically, I relied on results related to the first non-demographic question of
 13 the survey, which was as follows:

14 "The Census is an official population count that is conducted every 10
 15 years by the federal government. It requires all households to list the
 16 name, age, and race or ethnicity of every person living in the home and
 17 provide that information to the Census Bureau either online, by mail, or
 18 in-person with a census taker. The Census is required to keep this
 19 information confidential, and every single household in the country is
 20 required to participate.

21 In March 2020 you will receive an invitation from the U.S. Census to
 22 fill out the census form. Do you plan to participate and submit your
 23 household information?"

24 30. Response options for this question were "Yes, will participate" or "No, will NOT
 25 participate." The description of the Census provided in this question approximates the
 26 demographic information requested in the 2010 Census. The "Yes, will participate" response to
 27 this question indicates the population that would take the 2020 Census if a citizenship question
 28 was not included. All of my analyses based on survey data use this as the baseline responsive

1 population; individuals who are unlikely to respond to a 2010-style Census are excluded from my
2 analysis.

3 31. The second question in the Census 2020 Survey questionnaire asked the following:

4 “In 2020, the federal government is adding a new question to require
5 you to list whether you, and every person in your household is a U.S.
6 citizen, or not a citizen. With the addition of a citizenship question, will
7 you participate and submit your household information, or not?”

8 32. Response options for this question were the same as the first question: “Yes, will
9 participate” or “No, will NOT participate.” Using responses to this question, after isolating the
10 population who initially responds “Yes, will participate” to the first question, allows me to isolate
11 the effect of the addition of a citizenship question to the Census and its resultant effect on
12 response rates. Specifically, I was provided with estimates of the percent of respondents (and
13 accompanying uncertainty) who replied “No, will NOT participate” or refused to respond to the
14 second question after initially stating “Yes, will participate” to the first question.

15 33. Again, by removing from the analysis respondents who answered “No” or did not
16 respond to the first question (indicating that they would not respond to a 2020 Census even
17 without a citizenship question), I isolated the *specific* nonresponse attributable to the addition of a
18 citizenship question.

19 34. Scenario A is thus the projected population for each state, minus the mean rate of
20 drop-off due to the citizenship question.

21 35. In order to calculate Scenario A, I used two tables of survey data provided by Dr.
22 Barreto that reflect this drop-off from Question 1 to Question 2. Attached as **Exhibit C** to this
23 Declaration are true and correct copies of those data tables. Experts in this field would reasonably
24 rely on such tables when forming an expert opinion of this nature. These tables appeared as
25 Tables 12 and 13 in Appendix A of Dr. Barreto’s expert report in this action. *See* Expert Report
26 of Dr. Barreto, at pgs. 72-73 (PTX-499).

27 **2. Scenario B: Survey-based Nonresponse with Follow-up**

28 36. Scenario B builds on Scenario A, by accounting for initial non-respondents who may

1 later respond as a result of the Census Bureau's follow-up efforts. This is done using Question 8
2 on Dr. Barreto's survey:

3 "Now that you've heard a little bit about the 2020 Census let me ask you
4 one final question about how likely you are to participate. If the
5 government decides in 2020 to include a question about citizenship
6 status, and asks you to report the race, ethnicity, age, gender and
7 citizenship status of people living in your household, and the
8 government provides assurances that your information will be kept
9 confidential and ONLY used for purposes of counting the total
10 population and nothing more, would you participate and fill out the 2020
11 Census form, or not?"

12 37. Dr. Barreto's report states that this question may be considered a "Simulated Follow
13 Up" as it may "mimic an attempt at re-contact in the real world in a condensed telephone
14 interview setting, by allowing some time to pass, and then asking the same subjects their
15 willingness to participate a second or third time." Again, response options were "Yes, will
16 participate" or "No, will NOT participate."¹⁰

17 38. Dr. Barreto reports that respondents who were considered drop-off respondents due to
18 the citizenship question in Scenario A, but then responded "Yes, will participate" to this follow-
19 up question may be considered a proxy for individuals who would be responsive to reasonable
20 follow-up efforts conducted by the Census and thus would be enumerated.

21 39. Scenario B thus removes the mean share of individuals who changed their mind and
22 decided to reply to the Census after the follow-up from the drop-off respondents identified in
23 Scenario A, reducing the size of the drop-off population.

24 40. When forming my expert opinion as to the undercount projection for Scenario B, I
25 relied on the data tables from Dr. Barreto in Exhibit C, as well as two additional tables. The
26 additional tables include the percentage of survey respondents who responded "Yes, will
27

28 ¹⁰ Dr. Barreto's expert report pg. 40-41 para 92, see also appx B (which is the actual
telephone survey instrument). (PTX-499.)

participate” on Question 8, after having responded “Yes, will participate” on Question 1, and “No, will NOT participate” or refusing to respond to Question 2. The response rates are broken down by ethnicity and, for the Latino and Asian respondents, by whether they those groups were foreign-born or U.S.-born. Attached hereto as **Exhibit D** is the spreadsheet I created that exactly reflects the data values in these tables, and that I used to perform my calculations for Scenario B. Experts in this field would reasonably rely on this type of data when forming an expert opinion of this nature.

3. Race, Ethnicity, and Nativity in the *Census 2020 Survey*

41. In addition to these questions, I used demographic information provided in the survey to estimate differential nonresponse by racial/ethnic group and nativity. The first question, regarding racial/ethnic group, asks “What do you consider your race or ethnicity to be?” with response options that can be translated into the racial and ethnic categories used by the Census Bureau.¹¹ The second question asks “Were you born in the United States, [if Latino “on the island of Puerto Rico,”] or in another country?” Hispanic and Asian survey respondents were separated into U.S.-born or Foreign (including Puerto Rico) born based on this question. I was provided with the mean rate of nonresponse under Scenario A and the mean rate of follow-up response under Scenario B for non-Hispanic Whites, non-Hispanic Blacks, native born Hispanics, foreign born Hispanics, native born Asians, foreign born Asians, and non-Hispanic Other Race individuals, along with associated measures of uncertainty in these estimates for each group.

B. Scenarios C and D: Estimating the Undercount Based on Census Analyses

42. Scenarios C and D make use of recent Census Bureau estimates of nonresponse due to the citizenship question as well as other data related to nonresponse follow-up (NRFU) success.

1. Scenario C

43. Scenario C reflects estimates of nonresponse due to the addition of the citizenship

¹¹ For the purposes of this analysis, individuals identifying as “Hispanic/Latino” were classified as “Hispanic,” even if choosing an additional racial/ethnic group. Individuals marking multiple categories other than Hispanic, or the categories of “Middle Eastern or Arab,” “American Indian/Native American,” or “Other” were classified as “Other.”

1 question contained in an August 6, 2018 report produced by the Census Bureau, hereafter referred
2 to as the “Brown report.”¹²

3 44. The Brown report includes an analysis of housing unit self-response rates to the 2016
4 American Community Survey (ACS) questionnaire and the 2010 Census. The 2016 ACS is a
5 Census Bureau product that includes 75 questions, including a citizenship question. The 2010
6 Census was substantially shorter (10 questions) and did not include a citizenship question. In this
7 Census Bureau report, the authors are able to observe which housing units replied to the 2010
8 Census but not the 2016 ACS on the first mailing, providing an opportunity to observe the rate of
9 drop-off for a Census product with a citizenship question.

10 45. The authors of the Brown report construct a statistical model that seeks to isolate the
11 specific impact of having at least one non-citizen in the household (“noncitizen household”) on a
12 household’s drop-off rate, removing the effect of “race/ethnicity, age, educational attainment,
13 household income, working in the last week, job search in the last four weeks, and English
14 language ability” on drop-off rates, and comparing drop-off for noncitizen households to
15 households where all enumerated persons have been identified as citizens (“citizen
16 households”).¹³ They estimate a 5.8 percentage point difference in modeled (not actual) rates of
17 initial non-response for non-citizen households versus citizen households.¹⁴ Notably, this estimate
18 only captures part of the drop-off experienced by noncitizen households, and is not an estimate of
19 the overall rate of drop-off for noncitizen households which is likely higher. The authors of the
20 Brown report indicate a number of reasons suggesting why this “estimated effect on self response
21 . . . is conservative.”¹⁵

22 46. I used this 5.8% estimate of drop-off for noncitizen households from the Brown
23 report to estimate the undercount for Scenario C.

24
25
26 ¹² David J. Brown, Misty L. Heggeness, Suzanne M. Dorinski, Lawrence Warren, &
Moises Yi, *Understanding the Quality of Alternative Citizenship Data Sources for the 2020*
27 *Census*, August 6, 2018. (PTX-160; AR COM_DIS00009833.)

28 ¹³ *Id.* at 36-37.

¹⁴ *Id.* at 39.

¹⁵ *Id.*

1 **2. Scenario D**

2 47. Scenario D builds on Scenario C, by factoring in estimates of the success rate of
3 NRFU efforts.

4 48. For Scenario D, I used the 5.8% drop-off estimate for noncitizen households from
5 Scenario C, but reduced this figure by an estimate of NRFU success based on Census data and
6 analyses. The NRFU enumeration success rate I was provided with was 86.63%. Thus, Scenario
7 D constitutes the multiplication of the drop-off estimate by the 86.63% NRFU enumeration
8 success rate.

9 49. The 86.63% NRFU success rate figure I used for Scenario D was provided to me by
10 Plaintiffs' counsel and is a figure appearing in the expert report of Colm O'Muircheartaigh.
11 According to Dr. O'Muircheartaigh's report, that figure represents the Computer Assisted
12 Personal Interviewing Operation follow-up response rate in the 2016 American Community
13 Survey for census tracts with a higher than national average share of households containing at
14 least one non-citizen.¹⁶

15 **C. American Community Survey (ACS) Data**

16 50. In order to produce measures of the undercount under Scenarios A, B, C, and D, I
17 used state-level Census Bureau estimates of the population by the race, ethnicity, and nativity of
18 the householder¹⁷ or the presence of at least one non-citizen in the household. As of early
19 September 2018, the most recent Census product containing the requisite household-level
20 measures was the American Community Survey (ACS) 2016 1-Year Public Use Microdata
21 Sample (PUMS), which contains "a sample of actual responses to the American Community
22 Survey" and the survey weights necessary to make the sample representative of the national
23 population.¹⁸

24 51. To produce estimates under Scenario A and B, I extracted information about the race
25 of the householder, ethnicity of the householder, and for Asian and Hispanic householders, status

26 ¹⁶ Expert Report of Colm O'Muircheartaigh, at 10-11. (PTX-712.)

27 ¹⁷ Also called the "head of household."

28 ¹⁸ U.S. Census Bureau, American Community Survey Public Use Microdata Sample
(PUMS) Documentation, available at: <https://www.census.gov/programs-surveys/acs/technical-documentation/pums.html>. (PTX-540.)

as either foreign born or native born. I then mapped these householder characteristics onto the person-level ACS PUMS estimates to determine how many individuals live in households where the householder has said characteristics, aggregate to the state level using appropriate person-level weights, and derive the proportion of each state's total population whose householder falls into the following categories:

- non-Hispanic White
- non-Hispanic Black
- Foreign-born Hispanic
- Native-born Hispanic
- Foreign-born Asian
- Native-born Asian
- All other individuals ("Other")

52. The decision to use householder characteristics to estimate the population undercount is driven by Census practices for estimating non-response to the Census. Individuals receive the Census in the mail in a manner similar to receipt of the ACS, with a survey addressed "TO THE RESIDENT OF:" followed by the address of the respondent. For each household, the individual responding to the ACS is likely to be the individual who would have a major impact on the decision to have any individuals in the household enumerated via the 2020 Census.¹⁹ Thus, responses to the ACS regarding race or origins of the householder likely reflect the race or origins of the person who would be instrumental in the decision to participate in the Census, aligning well with the question wording and demographic characteristics available in the *Census 2020 Survey* used for Scenarios A and B.

53. For Scenarios C and D, I instead used ACS PUMS measures of whether or not there is at least one non-citizen in the household each person resides in.²⁰ Specifically, I separated households into two groups:

¹⁹ Individuals living in group quarters, constituting less than 10% of the U.S. resident population, were designated as the individuals responsible for deciding whether or not to respond to the Census.

²⁰ For individuals living in group quarters, constituting less than 10% of the U.S. resident population, the citizenship status of the individual was used instead.

- Households with at least one non-citizen (“noncitizen households”)
- All other households (“citizen households”)

54. This aligns with the method of distinguishing populations sensitive versus not sensitive to the addition of a citizenship question for the Brown report.²¹ Again, I mapped these household characteristics onto the person-level ACS PUMS estimates to determine how many individuals live in noncitizen versus citizen households, aggregate to the state level using appropriate person-level weights, and derive the proportion of each state’s total population whose household falls into the above categories.

55. Census Bureau-generated measures of uncertainty for these proportions are also included in my estimates of apportionment—see Section VI, *infra*—ensuring that even for states with small populations of particular racial/ethnic groups we may estimate the net undercount due to the addition of a citizenship question.

D. State-level Estimates of the Population Not Counted Due to a Citizenship Question

56. I combined the projections of the 2020 population by state in Table 2 of this report with the ACS PUMS estimates of the proportion of the population living in households with the characteristics outlined in the previous section. These were combined by multiplying the PEP-based 2020 population projections—which are based on the 2010 Census that did not include a citizenship question—by the ACS-based estimates of the *proportion* of the population that are living in households with those characteristics. The result is a 2020 estimate of the number of individuals in each household type, by state. I then subtracted a percentage of the population in each household type that would be undercounted in Scenarios A, B, C, and D. Finally, I re-aggregated these revised estimates of the population by household type back to state-level totals. In Table 3, I provide these estimates as the percent deviation from the 2020 Projection in Table 2 (here labeled “2020 Baseline”) for each undercount scenario.

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²¹ Brown et al., *supra*.

57. Table 3: Percent of Population Not Counted Due to a Citizenship Question

	2020 Baseline	Scenario A	Scenario B	Scenario C	Scenario D
Alabama	4,909,797	-6.19%	-2.73%	-0.24%	-0.03%
Alaska	742,898	-5.94%	-2.75%	-0.37%	-0.05%
Arizona	7,302,219	-7.44%	-3.94%	-0.96%	-0.13%
Arkansas	3,041,609	-6.11%	-2.80%	-0.37%	-0.05%
CALIFORNIA	40,393,990	-12.51%	-8.48%	-1.68%	-0.22%
Colorado	5,793,650	-6.77%	-3.53%	-0.70%	-0.09%
Connecticut	3,582,310	-6.56%	-3.31%	-0.72%	-0.10%
Delaware	984,226	-6.44%	-3.04%	-0.54%	-0.07%
District of Columbia	727,258	-7.22%	-3.29%	-0.72%	-0.10%
Florida	21,668,695	-7.27%	-3.61%	-0.99%	-0.13%
Georgia	10,696,376	-6.70%	-3.10%	-0.65%	-0.09%
Hawaii	1,434,604	-7.00%	-4.61%	-1.03%	-0.14%
Idaho	1,817,286	-5.99%	-2.92%	-0.44%	-0.06%
Illinois	12,710,600	-6.76%	-3.42%	-0.81%	-0.11%
Indiana	6,735,594	-5.90%	-2.79%	-0.35%	-0.05%
Iowa	3,182,422	-5.69%	-2.71%	-0.34%	-0.05%
Kansas	2,932,387	-6.16%	-3.01%	-0.52%	-0.07%
Kentucky	4,491,934	-5.65%	-2.60%	-0.22%	-0.03%
Louisiana	4,722,625	-6.40%	-2.82%	-0.24%	-0.03%
Maine	1,331,859	-5.36%	-2.46%	-0.19%	-0.03%
Maryland	6,136,606	-6.72%	-3.20%	-0.83%	-0.11%
Massachusetts	6,973,938	-6.25%	-3.17%	-0.81%	-0.11%
Michigan	10,041,036	-5.95%	-2.78%	-0.36%	-0.05%
Minnesota	5,672,759	-5.77%	-2.80%	-0.44%	-0.06%
Mississippi	2,981,765	-6.41%	-2.74%	-0.14%	-0.02%
Missouri	6,153,347	-5.80%	-2.67%	-0.24%	-0.03%
Montana	1,067,836	-5.46%	-2.45%	-0.14%	-0.02%
Nebraska	1,951,944	-6.07%	-2.95%	-0.52%	-0.07%
Nevada	3,158,362	-7.47%	-4.03%	-1.30%	-0.17%
New Hampshire	1,358,014	-5.50%	-2.61%	-0.28%	-0.04%
New Jersey	9,073,181	-7.02%	-3.73%	-1.11%	-0.15%
New Mexico	2,093,728	-8.78%	-5.01%	-0.69%	-0.09%
New York	19,917,386	-6.98%	-3.65%	-1.16%	-0.16%
North Carolina	10,515,309	-6.39%	-2.96%	-0.52%	-0.07%
North Dakota	783,517	-5.55%	-2.49%	-0.21%	-0.03%
Ohio	11,756,941	-5.79%	-2.66%	-0.21%	-0.03%
Oklahoma	4,000,423	-6.19%	-2.83%	-0.43%	-0.06%
Oregon	4,310,660	-6.13%	-3.06%	-0.65%	-0.09%
Pennsylvania	12,804,528	-6.00%	-2.87%	-0.34%	-0.05%
Rhode Island	1,064,874	-6.40%	-3.19%	-0.76%	-0.10%
South Carolina	5,201,635	-6.28%	-2.80%	-0.32%	-0.04%
South Dakota	889,060	-5.56%	-2.49%	-0.26%	-0.04%
Tennessee	6,826,163	-6.00%	-2.73%	-0.34%	-0.05%
Texas	29,403,076	-8.23%	-4.53%	-1.26%	-0.17%
Utah	3,211,388	-6.16%	-3.05%	-0.61%	-0.08%
Vermont	621,076	-5.38%	-2.51%	-0.17%	-0.02%
Virginia	8,629,657	-6.39%	-3.11%	-0.65%	-0.09%
Washington	7,617,840	-6.27%	-3.26%	-0.84%	-0.11%
West Virginia	1,781,002	-5.42%	-2.48%	-0.10%	-0.01%
Wisconsin	5,837,508	-5.83%	-2.79%	-0.33%	-0.04%
Wyoming	598,982	-5.86%	-2.83%	-0.23%	-0.03%

Note: 2020 Baseline is population projection to April 1, 2020 conducted by Bernard L. Fraga.

58. Table 3 indicates how much of each state's population would not be counted in the 2020 Census due solely to the addition of a citizenship question. The impacts are large for California, where 12.51% of the population would not be counted when using the survey-based estimates of nonresponse in Scenario A. This reduction is cut somewhat when the "Simulated Follow Up" is added, as in Scenario B the California undercount is 8.48%. In Scenario C, which is based on a Census analysis that only examines part of the total nonresponse for households with at least one noncitizen, the reduction in California's population is 1.68%. Scenario D, which builds on Scenario C by assuming a highly successful nonresponse follow-up operation for nonresponding households, California's population count is reduced by 0.22%.

59. Scenarios A and B show a greater decline than Scenarios C and D that are based on the Census analysis contained in the Brown report.²²

60. As explained, Scenarios C and D are based on a 5.8% estimate of drop-off for noncitizen households from the Brown report.²³ Those scenarios likely *underestimate* the actual non-response rate in 2020 due to the citizenship question.

61. First, According to Census Bureau Chief Scientist Dr. John Abowd, the 5.8 percentage point figure featured in the Brown report is "probably an underestimate" of the magnitude of nonresponse due to the addition of a citizenship question on the 2020 Census.²⁴ Indeed, Dr. Abowd goes on to state that it is likely that changes in response rates would occur for "all citizen households" as well: "If you ask us collectively do we think that the self-response of all citizen households is going to stay [un]changed in an environment where a controversial citizen question is on the census, we would say no."²⁵ Measures of nonresponse including "all citizen households" likely do a better job of capturing the full effect of the citizenship question on 2020 Census counts.

²² Brown et al., *supra*.

²³ *Id.* at 39.

²⁴ Deposition of Dr. John Abowd, August 29, 2018, pgs. 242-243. (PTX-500.)

²⁵ *Id.*

62. Second, the non-response rate estimated in the Brown report only includes non-citizen households and does not include any citizen households at all.²⁶ And, in turn, those non-citizen households are likely underrepresented in the ACS data I used to generate the proportion of non-citizen households in each state.²⁷ This is because, as the Brown report explains, self-responses to the ACS citizenship question skew in the direction of *underreporting* the presence of a noncitizen in the household.²⁸ As a consequence, Scenarios C and D do not take into account any all-citizen households or any non-citizen households that had self-reported as citizen households on the ACS.

63. Third, as the number of individuals in households with racial/ethnic, nativity, and citizenship characteristics associated with sensitivity to the citizenship question is based on the 2016 ACS, and will likely grow by April 2020, the estimates I produced generate less of an undercount than would be observed with population estimates more proximate to 2020.

64. Across all four of the scenarios, California loses a greater share of its population than any other state when a citizenship question is placed on the 2020 Census. In addition, under any uniform NRFU success rate (less than 100%) applied to Scenarios A or C, **California will always have the largest undercount of all of the states due to the citizenship question.** Thus, even if the uniform NRFU success rate were greater than 86.63% (but still less than 100%), California would still suffer the largest differential undercount.

65. Any uncertainty or estimation error in my baseline population projections would not affect whether there would be an undercount in Scenarios C or D because estimates of the baseline population are calculated independently from the calculations of the percentage point drop-off due to the addition of the citizenship question. For example, if the actual baseline enumerated California 2020 population were substantially larger than 40,393,990, there still would be a net undercount of this higher value because, according to the ACS, California has the

²⁶ *Id.* at 34.

²⁷ *Id.* at 20-21.

²⁸ *Id.* at 21 (“Discrepancy rates are higher for those individuals identified as U.S. noncitizens in administrative records This implies that ACS estimates of the U.S. citizen population are higher than they would be if one were to use currently available administrative records.”).

1 most noncitizen households and a uniform noncitizen-household drop-off rate (5.8%) would still
 2 be applied to California's non-citizen households. Therefore, California's undercount would still
 3 be the largest of all the states regardless of the margin of error on the population estimates.

4 **VI. QUANTIFYING THE IMPACT OF A CITIZENSHIP QUESTION ON CONGRESSIONAL** 5 **APPORTIONMENT**

6 66. Finally, I used the undercount estimates to quantify the impact of the addition of a
 7 citizenship question to the 2020 Census on congressional apportionment. Using the population
 8 projections and measures of uncertainty in the projections discussed in Section IV, *supra*, and the
 9 scenarios of nonresponse and follow-up with the attendant measures of uncertainty outlined in
 10 Section V, *supra*, I sought to quantify the probability that an undercount of California residents
 11 attributable to the addition of a citizenship question to the 2020 Census would impact California's
 12 congressional apportionment.

13 **A. Estimating 2020 Congressional Apportionment with a Citizenship** 14 **Question**

15 67. Apportionment is mandated by the Constitution, and determined based on the total
 16 population of each state. Since 1941, the formula used to determine how many congressional
 17 seats are apportioned to each state uses the "Method of Equal Proportions."²⁹ To compute
 18 apportionment using this method, each state is first apportioned a single, constitutionally-
 19 mandated seat, and then additional seats are distributed to each state in order of "priority."
 20 Priority is calculated as the state's population multiplied by the reciprocal of the geometric mean
 21 for each seat the state could receive, or $1/\sqrt{n(n-1)}$ (also called a "multiplier") for all n seats
 22 that could be assigned to a state. The resultant 385 highest "priority values" are apportioned
 23 seats.³⁰ The total number of seats assigned to each state constitutes apportionment.

24 68. California currently has the largest number of seats, with 53. What this means is that
 25 the multiplier for a 53rd seat, or $1/\sqrt{53(53-1)}$ (0.0190484829) times the apportionment

26 ²⁹ U.S. Census Bureau, Congressional Apportionment, Computing Apportionment,
 27 available at: <https://www.census.gov/population/apportionment/about/computing.html>. (PTX-
 28 541.)

³⁰ 435 minus 50, because 50 seats are automatically assigned with the one seat minimum
 per state.

1 population of California (the “priority value”) in 2010 was higher than all of the other states’
2 priority values that had not yet been used to assign a seat.

3 69. The process of apportioning seats is somewhat complex and relatively small
4 differences in state populations can be the difference between one state receiving a seat and
5 another state receiving a seat. Thus, I developed an apportionment formula and tested this
6 formula to ensure that it always provided precisely correct multipliers, priority values, state
7 apportionment, and order of seats apportioned to states. I used apportionment population data for
8 the 1980, 1990, 2000, and 2010 Censuses to conduct this validation. In each case, the statistical
9 formula successfully replicated the exact apportionment circumstances for each year. Thus, the
10 model will accurately predict 2020 apportionment based on the input of apportionment
11 populations for each state.

12 70. The apportionment population is based on the resident population as enumerated by
13 the decennial census, but also includes the nonresident population of federal employees stationed
14 overseas as assigned to states. This includes overseas military and other governmental personnel,
15 is also included in apportionment totals. The estimates in Section IV, *supra*, do not include the
16 overseas resident population, which is allocated to states for apportionment purposes, but is not
17 included in the population count made by the Census because the Census only counts U.S.
18 residents. The PEP estimates and ACS estimates also do not seek to estimate the overseas military
19 and other governmental population. Therefore, I estimated the overseas U.S. military, federal
20 civilian employees, and dependents living with these groups based on change in this population
21 from 2000-2010 and information about military personnel stationed in foreign countries as
22 reported by the Department of Defense.

23 71. The Department of Defense estimates that in FY2010 there were 293,600 active duty,
24 reserve, and civilian personnel required to be stationed in foreign countries across the Army,
25 Navy, Marine Corps, and Air Force.³¹ The Department of Defense estimates that in FY2018 there
26 were 198,700 active duty, reserve, and civilian personnel required to be stationed in foreign

27 ³¹ Defense Manpower Requirements Report, Fiscal Year 2011, February 2011, pg. 16.
28 (PTX-542.)

1 countries across the Army, Navy, Marine Corps, and Air Force, a number which has remained
 2 relatively stable over the last three fiscal years.³² The apportionment figures provided by the
 3 Census Bureau indicate 1,042,523 federal employees, including military and non-military
 4 personnel, residing overseas. Thus in 2010 military personnel made up approximately 28% of the
 5 overseas population counted for apportionment, a population that declined by 32.3% from
 6 FY2010 to FY2018. Using the 2010 estimate of the overseas population as a baseline, I reduced
 7 this figure by 18.96% due to the decline in military stationed overseas.³³ This revised estimate is
 8 then allocated to each state based on the average of the Census 2000 and Census 2010 shares of
 9 the overseas population allocated to each state, assuming some reversion to the mean given
 10 changes in state population shares over the preceding 18 years and declines in the overseas
 11 military population since 2010.

12 72. I examined five apportionment scenarios in the same manner as Section V, *supra*: the
 13 baseline population projection with no citizenship question, and Scenarios A, B, C, and D, which
 14 use different assumptions and data sources to quantify the impact of a citizenship question on
 15 nonresponse and nonresponse follow-up in the 2020 Census. Estimates of the average outcomes
 16 of those five apportionment scenarios are reflected in Tables 4 and 4A.

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 24 ³² Defense Manpower Requirements Report, Fiscal Year 2018, December 2017, pg. 16.
 (PTX-543.)

25 ³³ The correct reduction should have been 9.1%. *See* Errata to Expert Report of Bernard L.
 26 Fraga. (PTX-532.) Tables 4, 4A, 5, and 6 were instead calculated using a 18.96% reduction to the
 27 overseas population. However, since the percent of the overseas population allocated to each state
 28 does not change, each state's proportion of the estimated 2020 overseas population is unaffected.
 Therefore, my conclusions do not change when using the 9.1% figure. This concurs with findings
 by Defendants' expert, Dr. Stuart D. Gurrea, who states "the use of a marginally different (higher)
 Baseline apportionment population is immaterial." (*See* Expert Report and Declaration of Stuart
 D. Gurrea, Ph.D. October 3, 2018, p. 21, PTX-604, PTX 751.)

73. Table 4: Change in Apportionment Due to a Citizenship Question (rounded average outcomes)

	2020 Baseline	Scenario A	Scenario B	Scenario C	Scenario D
Alabama	6	7	7	7	6
Alaska	1	1	1	1	1
Arizona	10	10	10	10	10
Arkansas	4	4	4	4	4
CALIFORNIA	53	50	50	53	53
Colorado	8	8	8	8	8
Connecticut	5	5	5	5	5
Delaware	1	1	1	1	1
Florida	28	28	29	28	28
Georgia	14	14	14	14	14
Hawaii	2	2	2	2	2
Idaho	2	2	2	2	2
Illinois	17	17	17	17	17
Indiana	9	9	9	9	9
Iowa	4	4	4	4	4
Kansas	4	4	4	4	4
Kentucky	6	6	6	6	6
Louisiana	6	6	6	6	6
Maine	2	2	2	2	2
Maryland	8	8	8	8	8
Massachusetts	9	9	9	9	9
Michigan	13	13	13	13	13
Minnesota	7	8	8	7	7
Mississippi	4	4	4	4	4
Missouri	8	8	8	8	8
Montana	1	2	2	1	1
Nebraska	3	3	3	3	3
Nevada	4	4	4	4	4
New Hampshire	2	2	2	2	2
New Jersey	12	12	12	12	12
New Mexico	3	3	3	3	3
New York	26	26	26	26	26
North Carolina	14	14	14	14	14
North Dakota	1	1	1	1	1
Ohio	15	16	16	16	15
Oklahoma	5	5	5	5	5
Oregon	6	6	6	6	6
Pennsylvania	17	17	17	17	17
Rhode Island	1	1	1	1	1
South Carolina	7	7	7	7	7
South Dakota	1	1	1	1	1
Tennessee	9	9	9	9	9
Texas	39	38	38	38	39
Utah	4	4	4	4	4
Vermont	1	1	1	1	1
Virginia	11	11	11	11	11
Washington	10	10	10	10	10
West Virginia	2	2	2	2	2
Wisconsin	8	8	8	8	8
Wyoming	1	1	1	1	1

74. Table 4A: Change in Apportionment Due to a Citizenship Question (unrounded average outcomes)

	2020	Scenario A	Scenario B	Scenario C	Scenario D
Alabama	6.3487	6.6807	6.6711	6.5164	6.3923
Alaska	1.0000	1.0000	1.0000	1.0000	1.0000
Arizona	9.7249	9.6856	9.7081	9.6838	9.7148
Arkansas	4.0000	4.0000	4.0000	4.0000	4.0000
California	52.9925	49.9972	50.4965	52.5004	52.9011
Colorado	7.8316	7.8984	7.8705	7.8437	7.8306
Connecticut	4.9989	4.9993	4.9994	4.9984	4.9985
Delaware	1.0000	1.0000	1.0000	1.0000	1.0000
Florida	28.4291	28.4863	28.5563	28.4052	28.4498
Georgia	14.0111	14.0712	14.0867	14.0222	14.0159
Hawaii	2.0000	2.0000	2.0000	2.0000	2.0000
Idaho	2.0445	2.2328	2.1617	2.0757	2.0518
Illinois	16.7591	16.8430	16.8388	16.7552	16.7554
Indiana	8.9935	9.0002	8.9977	8.9959	8.9930
Iowa	4.0001	4.0025	4.0002	4.0001	4.0000
Kansas	4.0000	4.0000	4.0000	4.0000	4.0000
Kentucky	6.0000	6.0000	6.0000	6.0000	6.0000
Louisiana	6.0027	6.0324	6.0310	6.0068	6.0029
Maine	2.0000	2.0000	2.0000	2.0000	2.0000
Maryland	8.0011	8.0060	8.0052	8.0003	8.0004
Massachusetts	9.0108	9.0649	9.0374	9.0091	9.0096
Michigan	13.0693	13.3026	13.2358	13.1083	13.0700
Minnesota	7.3566	7.7293	7.6278	7.4250	7.3461
Mississippi	4.0000	4.0000	4.0000	4.0000	4.0000
Missouri	8.0012	8.0257	8.0150	8.0029	8.0010
Montana	1.2741	1.7637	1.6606	1.4704	1.3256
Nebraska	2.9952	2.9993	2.9991	2.9978	2.9960
Nevada	4.0000	4.0000	4.0000	4.0000	4.0000
New Hampshire	2.0000	2.0000	2.0000	2.0000	2.0000
New Jersey	11.9849	11.9862	11.9862	11.9732	11.9823
New Mexico	3.0000	3.0000	3.0000	3.0000	3.0000
New York	26.1316	26.2109	26.2029	26.0207	26.0964
North Carolina	13.9151	13.9791	13.9784	13.9391	13.9176
North Dakota	1.0000	1.0000	1.0000	1.0000	1.0000
Ohio	15.3829	15.7760	15.6936	15.5255	15.3974
Oklahoma	5.0051	5.0401	5.0289	5.0072	5.0035
Oregon	5.9729	5.9940	5.9907	5.9811	5.9767
Pennsylvania	16.8790	17.0301	16.9901	16.9259	16.8760
Rhode Island	1.2160	1.4334	1.3829	1.2164	1.2098
South Carolina	6.9986	6.9998	6.9999	6.9994	6.9987
South Dakota	1.0000	1.0000	1.0000	1.0000	1.0000
Tennessee	8.9998	9.0063	9.0034	9.0002	8.9995
Texas	38.5737	38.2290	38.3584	38.4143	38.5653
Utah	4.0001	4.0027	4.0014	4.0001	4.0001
Vermont	1.0000	1.0000	1.0000	1.0000	1.0000
Virginia	11.1733	11.4185	11.3735	11.2207	11.1983
Washington	9.9999	10.0157	10.0071	10.0004	10.0012
West Virginia	2.0021	2.0688	2.0277	2.0070	2.0021
Wisconsin	7.9200	7.9883	7.9760	7.9512	7.9203
Wyoming	1.0000	1.0000	1.0000	1.0000	1.0000
TOTAL	435	435	435	435	435

75. The first column of Table 4 provides the baseline apportionment estimates for each state, using the statistical formula discussed above and the 2020 population projections from Table 3. In this baseline scenario, there are changes from 2010 apportionment due to growth of the population in some states and decline in other states. Notably, California's apportionment is unchanged from 2010 in this baseline 2020 Census scenario with no citizenship question: 53 congressional seats.

76. A citizenship question on the 2020 Census would have a disproportionate, negative impact on California's congressional apportionment. Using Scenario A, which accounts for rates of Census nonresponse due to the citizenship question by race, ethnicity, and nativity of the householder, California loses three seats versus the baseline 2020 scenario (and 2010 apportionment), dropping from 53 to 50 seats. No other state experiences more than a one seat decline under this scenario. Under Scenario B, which includes estimates of the success of a targeted nonresponse follow-up effort, California still loses three congressional seats versus the 2020 baseline. Again, no other state experiences more than a one seat decline under this scenario. For Scenarios C and D, where Table 3 indicated population declines were smaller, on average California continues to hold 53 seats. However, as the next section shows, the *probability* of losing at least one seat still increases substantially even with these more limited estimates of nonresponse.

77. Like Table 4, Table 4A shows the average apportionment outcomes witnessed under the baseline scenario with no citizenship question (2020 Baseline), followed by four scenarios of nonresponse and follow-up (Scenario A, Scenario B, Scenario C, or Scenario D), but without rounding the average apportionment to the nearest whole seat. In each of the four scenarios the average congressional apportionment for California decreases as compared to the baseline projection.

B. Probability That a Citizenship Question Will Reduce California's Congressional Apportionment

78. Tables 4 and 4A reflect estimates of the *average* apportionment under the baseline scenario of the 2020 Census without a citizenship question as well as under Scenarios A, B, C,

1 and D, which factor in the addition of the question. However, because small differences in the
2 apportionment population for each state may make a large difference in apportionment, estimates
3 of the *average* apportionment may not provide a complete picture of how much more *likely*
4 certain apportionment outcomes are.’

5 79. To identify the *probability* that apportionment would be affected by the addition of a
6 citizenship question, therefore, I accounted for uncertainty in the population projections,
7 demographic composition of each state, rate of nonresponse, and rate of follow-up to nonresponse
8 when calculating apportionment. This is achieved through the generation of 10,000 simulated
9 datasets where, for each state, each of these quantities is estimated via a draw from a normal
10 distribution with a standard deviation equal to the observed variation we see in these measures for
11 each state. Simulation is a technique useful when the underlying probability is unknown or
12 complex, as is the case with the multiple inputs to the apportionment formula and apportionment
13 itself where outcomes for each state are dependent on outcomes for other states. In this way,
14 simulation is a more appropriate method of accounting for the “margin of error” in my analysis
15 because it accounts for “margins of error” in multiple estimates simultaneously.

16 80. I conducted 10,000 simulations for each of the five scenarios—the baseline
17 population projection and Scenarios A, B, C, and D—reporting the mean result of these
18 simulations where appropriate and using the distribution of results to define the probability of
19 particular events occurring.

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81. Table 5: Probability of Losing One or More Congressional Seats

	2010 Seats	2020 Baseline	Scenario A	Scenario B	Scenario C	Scenario D
Alabama	7	65.13%	31.93%	32.89%	48.36%	60.77%
CALIFORNIA	53	26.14%	99.72%	98.69%	49.86%	29.96%
Connecticut	5	0.11%	0.07%	0.06%	0.16%	0.15%
Georgia	14	0.91%	0.67%	0.40%	0.64%	0.77%
Illinois	18	99.89%	99.18%	99.49%	99.82%	99.82%
Indiana	9	0.65%	0.06%	0.26%	0.41%	0.70%
Michigan	14	92.97%	69.74%	76.41%	89.16%	92.93%
Minnesota	8	64.34%	27.07%	37.22%	57.50%	65.39%
Nebraska	3	0.48%	0.07%	0.09%	0.22%	0.40%
New Jersey	12	1.66%	1.83%	1.72%	2.75%	1.89%
New York	27	80.77%	74.04%	74.54%	87.79%	83.40%
Ohio	16	61.70%	22.46%	30.71%	47.46%	60.27%
Pennsylvania	18	99.41%	93.96%	96.39%	98.92%	99.50%
Rhode Island	2	78.40%	56.66%	61.71%	78.36%	79.02%
South Carolina	7	0.14%	0.02%	0.01%	0.06%	0.13%
Tennessee	9	0.07%	0.00%	0.00%	0.00%	0.05%
Washington	10	0.12%	0.03%	0.03%	0.09%	0.05%
West Virginia	3	99.79%	93.12%	97.23%	99.30%	99.79%
Wisconsin	8	8.00%	1.17%	2.40%	4.88%	7.97%

Note: Only shows states where at least one seat was lost relative to 2010 apportionment in any of the 10,000 simulations.

82. Table 5 is similar to Table 4, but instead of providing the mean number of seats each state is apportioned, I provide the probability that each state will lose at least one seat for the baseline and four undercount scenarios. In Table 5 we see that the probability of California losing at least one congressional seat after the 2020 Census goes from moderately rare (26.14%) with no citizenship question to a rounded 100% probability under Scenario A. After an attempt at following up with voters, as in Scenario B, California still loses at least one seat 99% of the time. Scenarios C and D, which are based on Census analyses accounting for only a part of nonresponse in households with at least one noncitizen, still show that the probability of California losing one or more congressional seats nearly doubles to become a 50-50 chance under Scenario C and increases 15% under Scenario D. For no other state do we see changes in the probability of losing at least one seat shift nearly as much due to the addition of a citizenship question as it does for California. This indicates that the addition of a citizenship question, under any scenario, will make it more likely that California will lose at least one congressional seat after the 2020 Census.

83. Table 6: Probability of Losing Two or More Congressional Seats

	2010 Seats	2020 Baseline	Scenario A	Scenario B	Scenario C	Scenario D
CALIFORNIA	53	2.59%	95.20%	87.20%	9.92%	3.44%
Illinois	18	24.20%	16.52%	16.63%	24.66%	24.64%
Michigan	14	0.10%	0.00%	0.01%	0.01%	0.07%
New York	27	6.13%	5.11%	5.31%	10.17%	7.02%
Ohio	16	0.01%	0.00%	0.00%	0.00%	0.00%
Pennsylvania	18	12.69%	3.03%	4.60%	8.49%	12.90%

Note: Only shows states where at least two seats were lost relative to 2010 apportionment in any of the 10,000 simulations.

84. Table 6 shows the probability of each state losing two or more seats in 2020.

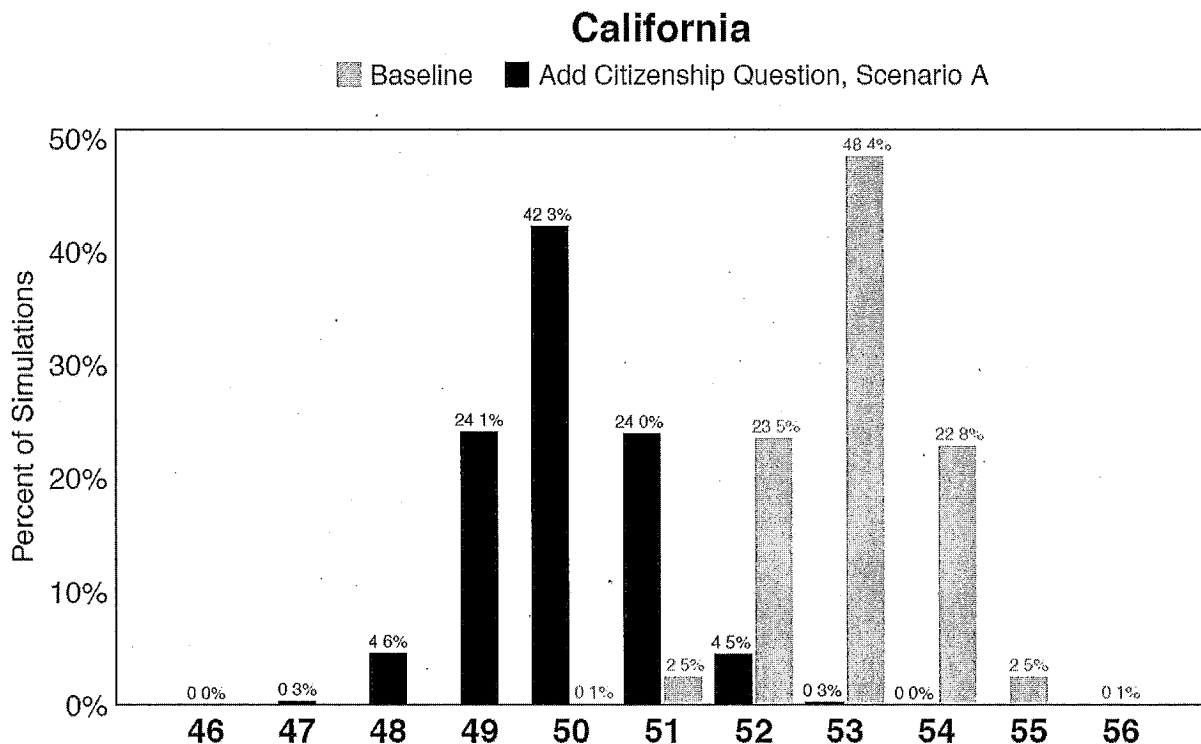
Examining results for California, we see that the chance of California losing two or more congressional seats after the 2020 Census goes from exceptionally rare (2.6%) in the baseline scenario with no citizenship question to almost guaranteed when a citizenship question is added under Scenario A (95.2%), or even after a reasonable attempt at following up with voters in Scenario B (87.2%). Scenarios C and D, which account for a portion of overall nonresponse attributable to a citizenship question, still indicate that the probability of California losing two or more congressional seats nearly triples under Scenario C and increases 33% under Scenario D *despite high rates of nonresponse follow-up success*.

85. California is the only state to be virtually guaranteed of losing two or more seats due to the addition of a citizenship question when using any of the undercount scenarios, and in addition to New York, is one of only two states to have a substantively significant increase in the probability of losing two or more seats under any of the undercount scenarios.

86. To fully visualize the range of possible apportionment outcomes for California, I provide charts showing the probability of each apportionment outcome. This constitutes a summary of 10,000 simulated apportionment outcomes for each scenario, again allowing me to account for multiple forms of uncertainty in the population, demographic, and nonresponse estimates. Most of the variation is due to uncertainty in the true population of California in 2020; substantial change in population trends could take place over the next three years, based on what was observed from 2007-2010. Thus, simulated outcomes of the 2020 apportionment range from

46 seats to 57 seats, but 95% of the estimates under either scenario apportion California between 48 seats and 54 seats.

87. Figure 1: Simulated Apportionment, Baseline vs. Scenario A

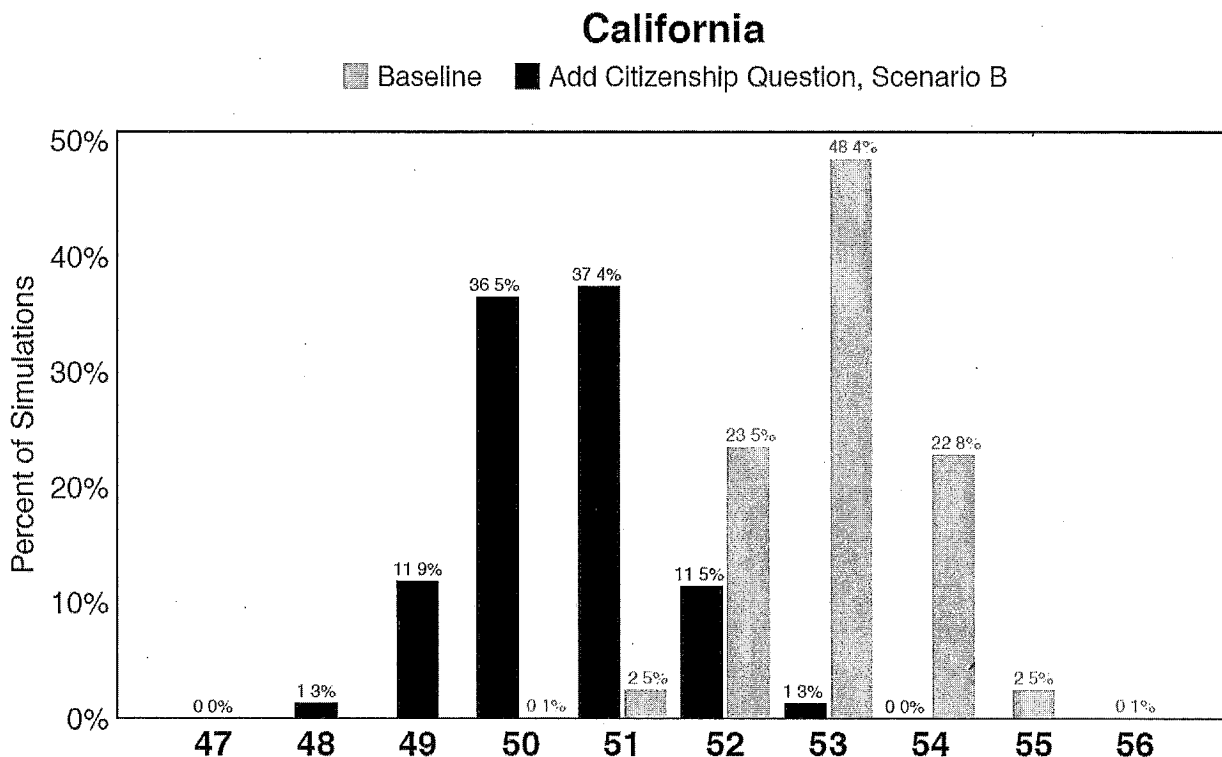


88. For Figure 1, these apportionment simulations were conducted under two conditions: a *Baseline* condition (depicted with gray bars) with no citizenship question on the 2020 Census, and an *Add Citizenship Question, Scenario A* condition (depicted with black bars) where a citizenship is incorporated into the 2020 Census under the assumptions of Scenario A and therefore the undercount increases substantially. In Figure 1, we see that for every potential apportionment outcome, the percent of simulations where California receives fewer seats than it currently has is greater in Scenario A than for the 2020 baseline. Furthermore, the percent of simulations where California receives more seats than it currently has is *smaller* in Scenario A than in the baseline estimate with no citizenship question. The percent of simulations where California's apportionment is 53 seats, the status quo after the 2010 Census, is virtually zero (0.3%) under Scenario A,³⁴ while the probability of California having at least 53 seats in the

³⁴ Even under the strictest standard measures of statistical significance, this is well beyond the "margin of error" and outside the "confidence interval."

1 baseline scenario is nearly 75%. Conversely, the probability of California losing 4 seats (thus
 2 dropping to 49 seats) seats under Scenario A is 24.1%, despite the fact that this never occurs in
 3 the baseline scenario.

4 89. Figure 2: Simulated Apportionment, Baseline vs. Scenario B



17 90. Figure 2 again presents the baseline scenario with no citizenship question (gray bars),
 18 but now compares this baseline to Scenario B where a citizenship question is on the 2020 Census,
 19 some individuals do not respond, but then an attempt at follow-up was estimated via the *Census*
 20 *2020 Survey* (black bars). As indicted in Tables 4, 5, and 6, the likelihood of California losing a
 21 large number of seats is reduced when accounting for follow-up. However, we still see that in
 22 only a very small number of scenarios (1.3%) California is apportioned the same number of seats
 23 in 2020 that it received in 2010. The probability of losing three or more seats is far higher
 24 (13.2%) and, again, for every potential apportionment outcome the percent of simulations where
 25 California receives fewer seats than it currently has is greater in Scenario A than for the 2020
 26 baseline.

VII. CONCLUSION

91. I conducted a statistical analysis of a series of relevant data sources in order to determine the impact of the addition of a citizenship question to the 2020 Census on population counts and congressional apportionment. Focusing on California, I found that the addition of a citizenship question to the 2020 Census would lead to a disproportionate reduction in California's population relative to other states. This disproportionate reduction means that the addition of a citizenship question would substantially increase the probability of a reduction of the number of congressional seats apportioned to California as part of the 2020 Census.

I reserve the right to amend or supplement my opinions if additional information or materials become available. I declare under penalty of perjury under the laws of the United States and the State of California that the foregoing is true and correct to the best of my knowledge

DATED: 12/27/2018

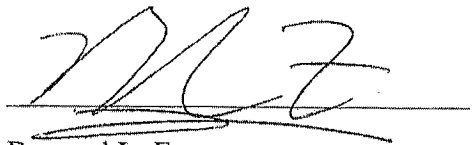

Bernard L. Fraga

EXHIBIT A

Bernard L. Fraga

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<i>Academic Affiliations</i>	Indiana University , Bloomington, IN Assistant Professor , Department of Political Science (2013 -) Faculty Affiliate , Center for Research on Race and Ethnicity in Society (2013 -) Faculty Affiliate , Latino Studies Program (2013 -)	
<i>Education</i>	Harvard University , Cambridge, MA Ph.D., Government and Social Policy (2013) A.M., Political Science (2011) Stanford University , Stanford, CA B.A., Political Science and Linguistics (2008) <i>Degree Conferred with Distinction and Departmental Honors</i>	
<i>Research Interests</i>	Electoral Politics, Institutions, and Policy - Race, Ethnicity, and Politics - Political Participation - Representation, Parties, and Partisanship - Campaigns - Political Geography	
<i>Book</i>	Fraga, Bernard L. (2018) <i>The Turnout Gap: Race, Ethnicity, and Political Inequality in a Diversifying America</i> . New York: Cambridge University Press.	
<i>Journal Articles</i>	Fraga, Bernard L. and Eitan D. Hersh. (2018) "Are Americans Stuck in Uncompetitive Enclaves? An Appraisal of U.S. Electoral Competition." <i>Quarterly Journal of Political Science</i> 13 (3): 291-311. Fraga, Bernard L. (2016) "Candidates or Districts? Reevaluating the Role of Race in Voter Turnout." <i>American Journal of Political Science</i> . 60 (1): 97-122. Fraga, Bernard L. (2016) "Redistricting and the Causal Impact of Race on Voter Turnout." <i>Journal of Politics</i> 78 (1): 19-34. Ansolabehere, Stephen and Bernard L. Fraga. (2016) "Do Americans Prefer Co-Ethnic Representation? The Impact of Race on House Incumbent Evaluations." <i>Stanford Law Review</i> 68 (6): 1553-1594. Fraga, Bernard L. and Julie Lee Merseth. (2016) "Examining the Causal Impact of the Voting Rights Act Language Minority Provisions." <i>Journal of Race, Ethnicity, and Politics</i> 1 (1): 31-59. Fraga, Bernard L. and Eitan D. Hersh. (2011) "Voting Costs and Voter Turnout in Competitive Elections." <i>Quarterly Journal of Political Science</i> 5 (4): 339-356.	

*Other
Publications*

- McElwee, Sean, Jesse H. Rhodes, Brian F. Schaffner, and Bernard L. Fraga. (2018) "The Missing Obama Millions." *New York Times*. March 10.
- Fraga, Bernard L., Sean McElwee, Jesse Rhodes, and Brian Schaffner. (2017) "Why did Trump win? More whites—and fewer blacks—actually voted." *Washington Post, Monkey Cage Blog*. May 8.
- Fraga, Bernard L. and Brian Schaffner. (2016) "Who's voting early? Latino turnout is surging, but white turnout is, too." *Washington Post, Monkey Cage Blog*. Nov 4.
- Fraga, Bernard L. (2016) Review of *American Identity and the Politics of Multiculturalism* by Jack Citrin and David O. Sears. *Perspectives on Politics* 14 (2): 562-564.
- Fraga, Bernard L. (2015) "The Voting Rights Act turns 50 today. Here are three trends in minority voting you should know about." *Washington Post, Monkey Cage Blog*. Aug 6.
- Fraga, Bernard L. (2013) "The SCOTUS Majority Is Missing Exactly What the VRA Sought to Remedy." *Monkey Cage Blog*. Jun 27.

*Working
Papers*

- "One Run Leads to Another: Minority Incumbents and the Emergence of Lower Ticket Minority Candidates" *with Eric Gonzalez Juenke and Paru Shah*
- "Are Minority Candidates Penalized by Party Politics? Race, Gender, and Access to Party Support and Donor Networks" *with Hans J.G. Hassell*
- "Who Does Voter ID Keep from Voting?" *with Michael G. Miller*
- "Using Nationwide Voter Files to Study the Effects of Election Laws" *with John B. Holbein and Christopher Skovron*
- "Measuring College Student Voter Turnout" *with John B. Holbein*
- "Evaluating Patterns in Women's Turnout at the State and District Level: Evidence from 2006-2016" *with Katelyn Stauffer*
- "Race, Party, and Candidate Prospects in the Multiple Stages of Congressional Elections"
- "How the Interplay between Individual and District Partisanship Affects Turnout" *with Daniel Moskowitz and Benjamin Schneer*
- "Abandoning (Partisan)ship? Dynamics of Latino Party Identification, 1989-2017" *with Colin Fisk*
- "Testing the 'Two Sides of Racialization'" *with Christopher DeSante and Matthew Hayes*
- "Panel Attrition in Voter Files: An Argument for Keeping Dropped Voters" *with Bradley Spahn and Alan N. Yan*
- "Winning the Race, Losing the Base? Minority Candidates and Electoral Competition"

Teaching

Indiana University, Bloomington, IN

Voting, Elections, and Public Opinion (*Undergraduate*)

Racial and Ethnic Politics in the U.S. (*Undergraduate*)
 Election Law and Voting Rights (*Undergraduate*)
 Analyzing Politics (*Undergraduate*)
 Electoral Politics and Political Participation (*Graduate*)
 The Politics of Race, Ethnicity, Gender, and Identity (*Graduate*)
 American Politics Workshop (*Graduate*)

Harvard University, Cambridge, MA

Teaching Fellow/Tutor, Sophomore Tutorial on Democracy (*Undergraduate*)
 Teaching Fellow, American Government (*Undergraduate*)

*Grants, Awards,
& Fellowships*

Midwest Political Science Association Latino Caucus Early Career Award (2018)
 Visiting Scholar (*non-residential*) (2017-2019)
 Institute for Democracy & Higher Education, Tufts University
 Indiana University Summer Instructional Development Fellowship (2017)
 New Initiatives Grant (2017)
 Massachusetts Institute of Technology Election Data and Science Lab
 Indiana University Latino Faculty and Staff Council Emerging Scholar Award (2017)
 Indiana University Trustees Teaching Award (2015)
 Midwest Political Science Association Lucius Barker Award (2015)
 Best Dissertation Award Honorable Mention (2014)
 American Political Science Association Race, Ethnicity, and Politics Section
 Harvard Graduate Prize Dissertation Completion Fellowship (2012-2013)
 Harvard University Center for American Politics Travel Grant (2012)
 Harvard University Certificate of Distinction in Teaching (2011, 2012)
 SSRC Graduate Studies Enhancement Grant (2010, 2011, 2012)
 NSF-IGERT Doctoral Fellow (2009-2011)
 Multidisciplinary Program in Inequality & Social Policy, Harvard University
 American Political Science Association Minority Fellow (2008-2010)
 Mellon Mays Undergraduate Fellowship (2006-2008)

*Conference &
Workshop
Presentations*

Invited Talk: University of Pittsburgh Seminar in Representation and Identity Politics. (Scheduled) "Separating Race and Party in Congressional Elections"

Invited Talk: Princeton Conference on Identity and Inequality. (Scheduled) “The Turnout Gap: Causes and Consequences of Racial/Ethnic Disparities in Voter Turnout”

American Political Science Association Annual Meeting, August 31, 2018. “Measuring College Student Voter Turnout” (*with John B. Holbein*)

Invited Talk: Spring Conference on American Politics, University of California San Diego Center for American Politics, May 24, 2018. “Who Does Voter ID Keep from Voting?”

Invited Talk: Race, Ethnicity, and Politics Workshop, Northwestern University, February 23, 2018. “The Turnout Gap: Causes and Consequences of Racial/Ethnic Disparities in Voter Turnout.”

Invited: Symposium Rapporteur for *The New American Electorate Beyond the Voting Booth: Building an Inclusive Democracy*, The Ohio State University, November 30 - December 1, 2017.

American Political Science Association Annual Meeting, September 1, 2017. “Are Minority Candidates Penalized by Party Politics? Race, Gender, and Access to Party Support and Donor Networks” (*with Hans J.G. Hassell*)

American Political Science Association Annual Meeting, September 1, 2017. “Mobilizing College Students through Peer-based Voter Registration Reminders.” (*with Katherine Hitchcock and Nina Wornhoff*)

Election Sciences, Reform, and Administration Summer Conference, July 27, 2017. “Panel Attrition in Voter Files: An Argument for Keeping Dropped Voters.” (*with Bradley Spahn and Alan Yan*)

Invited Talk: American Politics Workshop, Columbia University, April 25, 2017. “The Turnout Gap: Exploring the Causes and Consequences of Racial/Ethnic Differences in Voter Turnout.”

Midwest Political Science Association Annual Meeting, April 6, 2017. “Let’s Party: How the Interplay between Individual and District Partisanship Affects Turnout” (*with Daniel Moskowitz and Benjamin Schneer*)

Invited Talk: Research on Individuals, Politics, and Society Speaker Series, Vanderbilt University, February 27, 2017. “The Turnout Gap: Exploring the Causes and Consequences of Racial/Ethnic Differences in Voter Turnout.”

Invited Talk: Speaker Series, Rice University, January 27, 2017. “The Turnout Gap: Examining the Causes and Consequences of Racial/Ethnic Differences in Voter Turnout.”

American Politics Workshop, Indiana University, January 20, 2017. “The Turnout Gap: Race, Ethnicity, and Political Inequality in a Diversifying America.”

Invited Talk: ICPSR Summer Institute Blalock Lecture, August 4, 2016. "Using Big Data to Measure, Map, and Explain Racial Differences in Voter Turnout."

Midwest Political Science Association Annual Meeting, April 10, 2016. "Racial Coattails: How Top-Ticket Minority Candidates Affect the Emergence and Success of Lower Ticket Minority Candidates." (*with Eric Juenke and Paru Shah*)

Midwest Political Science Association Annual Meeting, April 10, 2016. "Robust Competition: The American Voter's Experience with Close Elections." (*with Eitan Hersh*)

Midwest Political Science Association Annual Meeting, April 8, 2016. "How Demographics and Geography Shape Minority Turnout Rates."

Workshop on Race, Ethnicity, and Migration, Indiana University, February 4, 2016. "How Age Shapes Minority Turnout Rates."

Invited Talk: American Politics Workshop, University of Chicago, Nov 9, 2015. "Changing Districts, Changing Turnout: Redistricting and Minority Political Participation."

American Politics Workshop, Indiana University, October 30, 2015. "Changing Districts, Changing Turnout: Redistricting and Minority Political Participation."

Midwest Political Science Association Annual Meeting, April 16, 2015. "Turning Sour Grapes into Wine: Voter Mobilization after Divisive Primaries."

Western Political Science Association Meeting, April 2, 2015. "Turning Sour Grapes into Wine: Voter Mobilization after Divisive Primaries."

Invited: Workshop Participant and Panelist, Harvard Kennedy School Ash Center for Democratic Governance and Innovation, March 26, 2015. "How Data is Helping Us Understand Voting Rights After *Shelby County v. Holder*."

Invited: Panelist, Neal-Marshall Black Culture Center, November 10, 2014. "Rights and Retrospectives: The Civil Rights Act at 50."

American Political Science Association Annual Meeting, Aug 30, 2014. "Examining the Causal Impact of the Voting Rights Act Language Minority Provisions." (*with Julie Lee Merseth*)

American Political Science Association Annual Meeting, Aug 29, 2014. "A Misreported Registration Gap? Race and Survey Misreporting of Voter Registration Status."

Midwest Political Science Association Annual National Conference, Apr 4, 2014. "Assessing the Causal Impact of Race-Based Districting on Voter Turnout." *Winner, Lucius Barker Award for best paper on a topic investigating race or ethnicity and politics and honoring the spirit and work of Professor Barker.*

Invited Talk: Social Science Research Commons Workshop in Methods, Indiana Uni-

versity, Dec 3, 2013. "Using the Catalist Database to Study Political Participation."

Politics of Race, Immigration, and Ethnicity Consortium Meeting, UC-Riverside, Sep 27, 2013. "Assessing the Causal Impact of Race-Based Districting on Voter Turnout."

Symposium on the Politics of Immigration, Race, and Ethnicity, Yale University, Oct 12, 2012. "Candidates or Influence? Reevaluating the Role of Race in Voter Turnout."

American Politics Research Workshop, Harvard University, Sep 18, 2012. "Candidates or Influence? Reevaluating the Role of Race in Voter Turnout."

Midwest Political Science Association Annual National Conference, Apr 13, 2012. "Candidates or Context? Evaluating the Determinants of Minority Voter Turnout."

American Politics Research Workshop, Harvard University, Oct 25, 2011. "Partisan Influence and Race in Congressional Elections."

American Political Science Association Annual Meeting, Sep 1, 2011. "Where's the Party? Partisan Influence and Race in Congressional Elections."

Political Psychology and Behavior Workshop, Harvard University, Mar 11, 2011. "Party Coalitions and Minority Candidate Emergence."

American Politics Research Workshop, Harvard University, Feb 24, 2011. "Group-Level Political Incorporation into Partisan Coalitions."

American Political Science Association Annual Meeting, Sep 3, 2010. "The (Surprising) Short-Term Impact of the Language Provisions of the VRA."

Political Psychology and Behavior Workshop, Institute for Quantitative Social Science, Harvard University, Mar 5, 2010. "Randomly Assigned Voting Costs in Competitive Elections." (*with Eitan Hersh*)

*Advising &
Service*

Ph.D. Dissertation Committee Chair and Member, *Indiana University* (2013 -)

Master's Thesis Examiner in Political Science, *Freie Universität Berlin* (2017-2018).

Faculty Mentor, Center for Research on Race and Ethnicity in Society Postdoctoral Scholar, *Indiana University* (2017 -)

Faculty Mentor, Center for Research on Race and Ethnicity in Society Undergraduate Research Program, *Indiana University* (2017 - 2018)

Honors Thesis Mentor, Department of Political Science, *Indiana University* (2014-2016, 2018 -)

Faculty Mentor, Cox Research Scholars Program, *Indiana University* (2013 -)

Member, Diversity and Affirmative Action Committee, Bloomington Faculty Council,

Indiana University (2016-2017)

Board Member, All In Campus Democracy Project and Big 10 Voting Challenge, *Indiana University* (2016, 2018)

Coordinator, Department of Political Science American Politics Subfield, *Indiana University* (2018 -)

Co-coordinator, Department of Political Science Political Analytics Program, *Indiana University* (2018 -)

Member, Department of Political Science Development Committee, *Indiana University* (2018-2019)

Member, Department of Political Science Personnel Committee, *Indiana University* (2017-2018)

Member, Department of Political Science Graduate Program and Admissions Committee, *Indiana University* (2013-2017)

Member, Department of Political Science Undergraduate Program Committee, *Indiana University* (2015-2016)

Member, Department of Political Science Graduate Awards Committee, *Indiana University* (2014-2015)

Member, Center for Research on Race and Ethnicity in Society Postdoctoral Fellowship Selection Committee, *Indiana University* (2014)

*Professional
Activities &
Affiliations*

Reviewer: *American Political Science Review*; *American Journal of Political Science*; *Journal of Politics*; *Journal of Race, Ethnicity, and Politics*; *Cambridge University Press*; *Oxford University Press*; *W. W. Norton & Co.*; *British Journal of Political Science*; *Political Analysis*; *Political Research Quarterly*; *Political Psychology*; *Public Opinion Quarterly*; *Legislative Studies Quarterly*; *Political Behavior*; *American Politics Research*; *Politics, Groups, and Identities*

Member, Western Political Science Association Committee on the Status of Latinos/as in the Profession (2017-2019, Chair 2018-2019)

Member, Executive Committee, Section on Race, Ethnicity, and Politics, American Political Science Association (2019-2021)

Member, Nominations Committee, Section on Race, Ethnicity, and Politics, American Political Science Association (2017-2019)

Research Affiliate, Democracy Fund Voter Study Group (2018 -)

Co-Organizer, Symposium on the Politics of Immigration, Race, and Ethnicity (SPIRE) (2016 -), Institution Host (2014)

Program Co-Chair, Election Sciences, Reform, and Administration (ESRA) Summer Conference (2017)

Chair, Lucius Barker Award Selection Committee, Midwest Political Science Association
(2017-2018)

Member: *American Political Science Association; Midwest Political Science Association;
Western Political Science Association*

EXHIBIT B

LIST OF SOURCES: TRIAL DECLARATION OF DR. BERNARD L. FRAGA

State of California, et al. v. Wilbur L. Ross, et al., No. 3:18-cv-01865

The following is a list of sources relied on by Dr. Bernard L. Fraga when forming his expert opinion, as articulated in his Trial Declaration:

Articles, Books, Reports, Documents

- Albert E. Fontenot, Jr., 2020 Census Program Memorandum Series: 2018.10, April 16, 2018, available at https://www2.census.gov/programs-surveys/decennial/2020/program-management/memo-series/2020-memo-2018_10.pdf (PTX-582)
- David J. Brown, Misty L. Heggeness, Suzanne M. Dorinski, Lawrence Warren, & Moises Yi, *Understanding the Quality of Alternative Citizenship Data Sources for the 2020 Census*, August 6, 2018 (PTX-160)
- Defense Manpower Requirements Report, Fiscal Year 2011, February 2011 (PTX-542)
- Defense Manpower Requirements Report, Fiscal Year 2018, December 2017 (PTX-543)
- Expert Report and Declaration of Christopher Warshaw, Ph.D., *New York Immigration Coalition v. United States Department of Commerce*, No. 1:18-cv-05025 (S.D.N.Y.), Sept. 7, 2018
- Expert Report of Bernard L. Fraga (PTX-530)
 - Supplement Report of Bernard L. Fraga (PTX-531)
 - Errata to Expert Report of Bernard L. Fraga (PTX-532)
 - Curriculum Vitae of Bernard L. Fraga (PTX-533)
- Expert Report of Dr. Colm O'Muircheartaigh (PTX-712)
- Expert Report of Dr. Matthew A. Barreto (PTX-499)
- Expert Report of Stuart Gurrea (PTX-751)
- Karen M. Mills, Census 2000 Brief, Congressional Apportionment, issued July 2001, available at <https://www.census.gov/population/apportionment/files/2000%20Apportionment%20Brief.pdf>

- Kristin D. Burnett, 2010 Census Briefs, Congressional Apportionment, issued November 2011, available at <https://www.census.gov/prod/cen2010/briefs/c2010br-08.pdf>
- Memorandum from Secretary Ross to Karen Dunn Kelley re Reinstatement of Citizenship Question on the 2020 Decennial Census Questionnaire (3/26/18) (PTX-026)
- Mikelyn Meyers, U.S. Census Bureau, Respondent Confidentiality Concerns in Multilingual Pretesting Studies and Possible Effects on Response Rates and Data Quality for the 2020 Census (May 16, 2018) (PTX-158)
- Rob J. Hyndman & George Athanasopoulos, *Forecasting: Principles and Practice* (2018), available at <https://otexts.org/fpp2/index.html>
- Thomas Mule, "Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Persons in the United States," DSSD 2010 Census Coverage Measurement Memorandum Series, 2010-G-01, May 22, 2012 (PTX-211)
- Thomas Mule, "Census Coverage Measurement Estimation Report: Summary of Estimates of Coverage for Housing Units in the United States," DSSD 2010 Census Coverage Measurement Memorandum Series, 2010-G-02, May 22, 2012
- U.S. Census Bureau, 2020 Census Detailed Operational Plan for: 18. Nonresponse Followup Operation (NRFU) (PTX-539)
- U.S. Census Bureau, American Community Survey Office, American Community Survey 2016, ACS 1-Year PUMS Files ReadMe, available at https://www2.census.gov/programs-surveys/acs/tech_docs/pums/ACS2016_PUMS_README.pdf?#
- U.S. Census Bureau, American Community Survey Public Use Microdata Sample (PUMS) Documentation, available at: <https://www.census.gov/programs-surveys/acs/technical-documentation/pums.html> (PTX-540)
- U.S. Census Bureau, Apportionment of the U.S. House of Representatives, available at <https://www.census.gov/prod/3/98pubs/CPH-2-US.PDF>
- U.S. Census Bureau, Center for Survey Measurement (CSM), Memorandum for Associate Directorate for Research and Methodology (ADRM) re: Respondent Confidentiality Concerns (Sept. 20, 2017) (PTX-307)
- U.S. Census Bureau, Congressional Apportionment, Computing Apportionment, available at: <https://www.census.gov/population/apportionment/about/computing.html> (PTX-541)

- U.S. Census Bureau, Data, State Population Totals and Components of Change: 2010-2017, available at: <https://www.census.gov/data/datasets/2017/demo/popest/state-total.html>
- U.S. Census Bureau, Data Sets, available at: <https://www2.census.gov/programs-surveys/popest/datasets/2000-2007/state/asrh>
- U.S. Census Bureau, Methodology for the Intercensal Population and Housing Unit Estimates: 2000 to 2010 (Revised October 2012), available at: <https://www2.census.gov/programs-surveys/popest/technical-documentation/methodology/intercensal/2000-2010-intercensal-estimates-methodology.pdf> (PTX-537)
- U.S. Census Bureau, “Methodology for the United States Population Estimates: Vintage 2017, Nation, States, Counties, and Puerto Rico – April 1, 2010 to July 1, 2017” (PTX-782)
- U.S. Census Bureau, Population and Housing Unit Estimates, available at: <https://www.census.gov/programs-surveys/popest.html>
- U.S. Census Bureau, Population and Housing Unit Estimates, Frequently Asked Questions, available at: <http://www.census.gov/programs-surveys/popest/about/faq.html> (PTX-583)

Other Materials

- 00pvalues.txt [FRAGA_00001] (PTX-544)
- 90pvalues.txt [FRAGA_00002] (PTX-545)
- 1970a_us1-03.pdf [FRAGA_00003-FRAGA_00033] (PTX-546)
- 1970a_v1pAs1-01.pdf [FRAGA_00034-FRAGA_00065] (PTX-547)
- 2000PHC3TableA.pdf [FRAGA_00066] (PTX-548)
- PUMSDataDict16.pdf [FRAGA_00067-FRAGA_00212] (PTX-549)
- sc-est2007-alldata6.pdf [FRAGA_00213-FRAGA_00214] (PTX-550)
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- 2010CensusOverseasCounts.xlsx [FRAGA_00217] (PTX-552)
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- ApportionmentPopulation2010.xlsx [FRAGA_00219] (PTX-554)
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- tab03.xls [FRAGA_00223] (PTX-558)
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- FRAGA_00226_Apportion_Function.R [FRAGA_00226] (PTX-561)
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- FRAGA_00231_LongScript_Scenario3.R [FRAGA_00231] (PTX-566)
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- FRAGA_00233_NonCitizenHouse_Proportions.csv [FRAGA_00233] (PTX-568)
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- FRAGA_00236_ResponseRates_Scenario1.csv [FRAGA_00236] (PTX-571)
- FRAGA_00237_ResponseRates_Scenario2_NRFU.csv [FRAGA_00237] (PTX-572)
- FRAGA_00238_ResponseRates_Scenario3.csv [FRAGA_00238] (PTX-573)
- FRAGA_00239_ResponseRates_Scenario4_NRFU.csv [FRAGA_00239] (PTX-574)
- FRAGA_00240_Seats_80-10.csv [FRAGA_00240] (PTX-575)
- FRAGA_00241_State Names Merge Dictionary.csv [FRAGA_00241] (PTX-576)
- FRAGA_00242_Table1.R [FRAGA_00242] (PTX-577)

- FRAGA_00243_Table2.R [FRAGA_00243] (PTX-578)
- FRAGA_00244_Table3.R [FRAGA00244] (PTX-579)
- FRAGA_00245_Table456.R [FRAGA00245] (PTX-580)
- FRAGA_00246_PC80-1-A1.pdf [FRAGA00246-FRAGA00561] (PTX-581)

EXHIBIT C

DATA TABLES FROM EXPERT REPORT OF DR. MATTHEW A. BARRETO*State of California, et al. v. Wilbur L. Ross, et al.*, No. 3:18-cv-01865

Table 12: California Subset — Estimated Drop-off Rate From Q1-Q2 (Only Among Those Who Say Yes on Q1)

	Estimate	Lower	Upper	S.E.	Sig
Full Sample	0.1227786	0.1050600	0.1404971	0.0107712	99.99
Non-Latino	0.0858753	0.0680105	0.1037401	0.0108601	99.99
Latino	0.1957771	0.1580658	0.2334883	0.0229248	99.99
Foreign Born	0.1937608	0.1530296	0.2344921	0.0247606	99.99
US Born	0.1977544	0.1344262	0.2610825	0.0384974	99.99
Asian	0.0429115	0.0100142	0.0758089	0.0199984	98.40
Foreign Born	0.0319674	-0.0005842	0.0645191	0.0197882	94.70
US Born	0.0754759	-0.0116071	0.1625589	0.0529380	92.30
Black	0.0313627	-0.0015218	0.0642473	0.0199906	94.20
White	0.0971811	0.0746701	0.1196920	0.0136845	99.99
Other	0.1980445	0.0810896	0.3149994	0.0710972	99.70

Table 13: Non-California — Estimated Drop-off Rate From Q1-Q2 (Only Among Those Who Say Yes on Q1)

	Estimate	Lower	Upper	S.E.	Sig
Full Sample	0.0649230	0.0558447	0.0740014	0.0055187	99.99
Non-Latino	0.0570172	0.0473925	0.0666420	0.0058509	99.99
Latino	0.1220957	0.0956436	0.1485477	0.0160803	99.99
Foreign Born	0.1145051	0.0835845	0.1454257	0.0187967	99.99
US Born	0.1278796	0.0875983	0.1681609	0.0244871	99.99
Asian	0.0730746	0.0160719	0.1300772	0.0346521	98.30
Foreign Born	0.0716425	0.0037076	0.1395775	0.0412978	95.90
US Born	0.0776782	-0.0258946	0.1812511	0.0629622	89.10
Black	0.0784156	0.0439822	0.1128490	0.0209322	99.99
White	0.0520339	0.0421279	0.0619398	0.0060218	99.99
Other	0.0622659	0.0236780	0.1008539	0.0234577	99.60

EXHIBIT D

State	Asian_u		Asian_nrf		Latino_u		Latino_nrf		Latino_US_n		Other_nrfu		White_nrfu		Asian_F_sd		Asian_US_sd		Black_sd		Latino_F_sd		Latino_US_sd		Other_sd		White_sd		
	u		u		u		u		u		u		u		u		u		u		u		u		u		u		
Alabama	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Alaska	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Arizona	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Arkansas	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
California	0	0.2966409	0.4479022	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.2966409	0.4479022	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Colorado	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Connecticut	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Delaware	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
District of Columbia	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Florida	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Georgia	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Hawaii	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Idaho	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Illinois	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Indiana	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Iowa	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Kansas	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Kentucky	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Louisiana	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Maine	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Maryland	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Massachusetts	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Michigan	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Minnesota	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Mississippi	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Missouri	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Montana	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Nebraska	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
Nevada	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
New Hampshire	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
New Jersey	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
New Mexico	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	
New York	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773									

Pennsylvania	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Rhode Island	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
South Carolina	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
South Dakota	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Tennessee	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Texas	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Utah	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Vermont	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Virginia	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Washington	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
West Virginia	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Wisconsin	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276
Wyoming	0.0039901	0	0.6215541	0.4730633	0.3216129	0.7475773	0.5464857	0.063041	0	0.1749581	0.1732567	0.1295335	0.4322288	0.0717276

CERTIFICATE OF SERVICE

Case Name: **State of California, et al. v.** No. **3:18-cv-01865**
Wilbur L. Ross, et al.

I hereby certify that on December 28, 2018, I electronically filed the following documents with the Clerk of the Court by using the CM/ECF system:

TRIAL DECLARATION OF BERNARD L. FRAGA, PH.D.

I certify that **all** participants in the case are registered CM/ECF users and that service will be accomplished by the CM/ECF system.

I declare under penalty of perjury under the laws of the State of California the foregoing is true and correct and that this declaration was executed on December 28, 2018, at Sacramento, California.

Eileen A. Ennis
Declarant

/s/ Eileen A. Ennis
Signature

SA2018100904